APPLICATION OF MULTI – STEP TIME SERIES PREDICTION FOR INDUSTRIAL EQUIPMENT PROGNOSTIC

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Application of multi-step time series prediction for industrial equipment prognostic

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***Abstract*—The use of prognostics is critically to be implemented in industrial. This paper presents an application of multi-step time series prediction to support industrial equipment prognostic. An artificial neural network technique with sliding window is considered for the multi-step prediction which is able to predict the series of future equipment condition. The structure of prognostic application is presented. The feasibility of this prediction application was demonstrated by applying real condition monitoring data of industrial equipment.**

Keywords-component; prognostic; neural network; failure propability; time series prediction; multi-step prediction

I. INTRODUCTION

Prognostics have gained popularity and play a pivotal role in predicting the behavior of industrial equipment. Generally, prognostics is referred because of its ability to predict the condition of observed system based upon the current and past condition data [1]. In prognostics study, the goal is to estimate the Remaining Useful life (RUL), which to measure the time left from the normal operation until breakdown occur or machine condition reaches the critical failure threshold [1]. As most of the mechanical equipment usually will go through a measureable process of degradation before the failures occur[2], prognostics becomes an essential function to orderly deliver failure information in advanced to the maintenance engineers to have sufficient time to adjust their production line flow and prepare the maintenance necessary action .

In general, prognostics can be divided into three main approaches: model-based, experience–based, and data-driven prognostics [3]. Model-based prognostics approach requires the consistence of mathematical model based on the physical fundamentals of an observed system. Experience-based prognostics involve in collecting and analyzing statistical information to indicate survival of system based upon the expert judgment. Data-driven prognostics require and utilizes large amount of current and past data to generate the prognostics model that learns the behavior of the observed system. In this paper, data-driven approach is addressed in order to utilize the availability of condition data in the most advanced machine in industry.

II. RELATED STUDY

With the increase of sophisticated monitoring sensor installment in industrial equipment, many applications of data-driven prognostics approach using condition monitoring data has been developed [2-5]. Signals sensor which typically correlated with the degradation process can be used for generating the prognostics model and estimating the remaining useful life of the observed equipment. Therefore data-driven prognostics development requires huge data which ranging from the normal condition until failure condition.

However, in practice, the equipments are hardly vulnerable to final failure and it is difficult to develop the appropriate prognostics model. Therefore, some studies use the typical failure distribution such as exponential or normal distribution to model the degradation process and estimate RUL [5][6]. Furthermore, Caesarendra et al. [7] assessed the equipment condition by using a pre-specified failure threshold to identify normal and failure condition for generating the degradation model and calculating RUL between the pre-specified failures. A work by Heng et al. [8] also addressed that in the real environment, the equipment are rarely allowed to run to failure and hence the data for prognostics are commonly suspended.

One of the solutions to predict the failure of the equipment is by applying the time series technique. The technique is able to establish the model that describes relationship of the degradation condition with a function of time. In addition, this model is used to extrapolate the series of degradation value into the future time [9]. As a result, the information of RUL can be obtained in advanced and hence providing sufficient time to make the decision whether to continue or stop the operation of equipment. Several studies wisely applied the time series techniques in the prognostic approach. As an example, [4] uses Autoregressive Moving Average (ARMA) model for predicting the series of failure probabilities in order to estimate the RUL at the future failure time. However, most of these predictions techniques are based on linear model, in which are unfavorable to most industrial processes that are inherently nonlinear.

Neural networks are very useful for nonlinear system modeling and offer better prediction result [10]. However, there are minimum prognostics applications that capitalize neural networks for extrapolating equipment condition and estimating their RUL. Therefore, in this paper an application of multi-step time series prediction is introduced for supporting equipment prognostic using neural networks. The paper also presents two types of multi-step prediction strategies in order to estimate the RUL of the observed equipment.

III. ARTIFICAL NEURAL NETWORK

A. Overview

Artificial Neural Networks (ANNs) are biologically inspired computer programs which are designed to simulate similar mechanism of human brain information processing [11]. By using the concept of learning through experience, ANNs gather the knowledge and then detect the patterns and relationship in data. The ANNs structure constitutes as a computational model that contains hundreds of artificial neurons and connects with coefficients known as weights[11]. Fig. 1 shows the model of an ANN structure. The input signals, $x_1, x_2, \ldots x_n$ are propagated through the network with the weight. The weight $w_1, w_2, \ldots w_n$ are for connection between neurons input and neuron hidden, and the combination of input signals and weights are passed through an activation function to produce the output value of the neuron y_k.

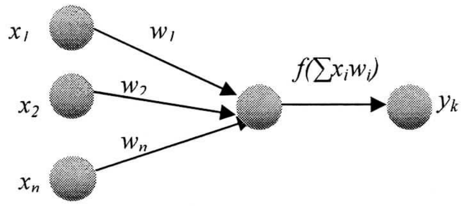

Figure 1. Example of a nonlinear model of a neural network

B. Feedforward Neural Network

Artificial Neural Networks have been widely applied in time series prediction[10]. In this paper, the time series prediction model applied feedforward neural networks (FFNN) and employed a sliding window over the input sequence. In order to construct the multi-step prediction, the model employs previous predicted value to forecast the future values iteratively until the expected future values are obtained. This prediction process can be illustrated generally in Fig. 2.

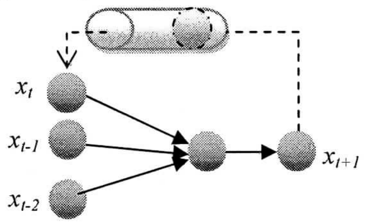

Figure 2. The concept of multi-step prediction

In this work, two strategies of multi-step prediction for predicting the future equipment condition are provided as follows:

1) d-step prediction

This strategy is able to predict a series of predicted value based on the required time step. In predicting d values, the prediction model utilizes the previous values to forecast iteratively of the future d values. Given the observation, $y_t = [x_{t-r+1}, x_{t-r-2} \ldots, x_t]$ the first future value can be predicted by using:

$$\hat{y}_{t+1} = f(y_t) = f(x_{t-r+1}, x_{t-r+2} \ldots, x_t) \tag{1}$$

where r denotes the number of inputs or the size of sliding window dimension. For predicting the next value, the same prediction model can be given:

$$\hat{y}_{t+2} = f(x_{t-r+2}, x_{t-r+3} \ldots, \hat{y}_{t+1}) \tag{2}$$

Then, the procedure repeats recursively depending on the required number of time series.

$$\hat{y}_{t+d} = f(x_{t-r+d}, x_{t-r+d+1)+} \ldots, \hat{y}_{t+d-1}) \tag{3}$$

2) Predefine z-treshold

A recursive multi-step prediction also can predict the output until the predefined value achieved. This strategy is similar to above strategy except the process of prediction requires predefined value for stopping criterion of multi-step prediction. Hence, (3) can be found to satisfy:

$$\hat{y}_{t+d} = f(x_{t-r+d}, x_{t-r+d+1)+} \ldots, \hat{y}_{t+d-1}) \rightarrow z, z \leq 1 \tag{4}$$

In this strategy, if the required predicted value z is known, it would be possible to characterize the future series of predicted value until z. By practice, the prediction process from the beginning until the final of failure probabilities is considered rather than deciding the number of time steps for estimating RUL of equipment. In the following section, a methodology to develop the proposed prognostic application for industrial equipment is described.

IV. METHODOLOGY

The methodology for developing the prognostic application for industrial equipment is illustrated in the Fig. 3.

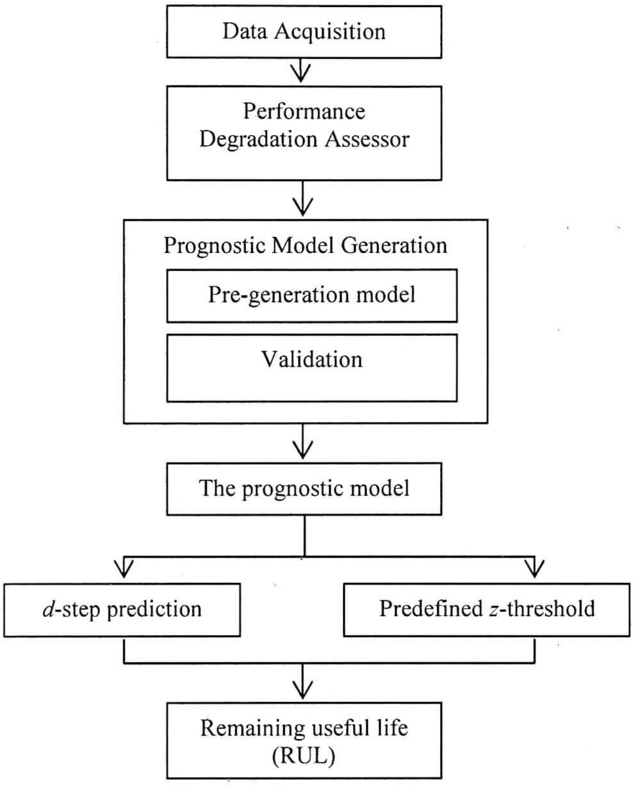

Figure 3. The methodology of industrial equipement prognostics

A. Data Acqusition

In order to get the data, the readily condition monitoring data from the observed equipment is extracted from equipment database. The selection of condition data to be the prognostic parameter is very crucial. Hence, the knowledge of equipment experts are deployed in order to reveals the most appropriate condition parameters.

B. Performance Degradation Assessor

In the proposed prognostics method, the condition monitoring data that are determined by the experts will be transformed into failure probabilities (FPs). The goal of this transformation is to calculate the probabilistic degradation of the observed equipment. This transformation allows us to use logistic regression based on the following equation:

$$p(x) = \frac{e^{g(x)}}{1+e^{g(x)}} = \frac{1}{1+e^{-g(x)}} \qquad (5)$$

where *p(x)* is the probability of failure, *x* is an input vector corresponding to the independent variable and *g(x)* is the logit model which can be defined as:

$$g(x) = \log\left(\frac{p(x)}{1-p(x)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \qquad (6)$$

where *g(x)* is a linear combination of independent variables, α is the intercept when $x=0$ and βs are known as the regression coefficients, which can be estimated using a mathematical technique called Maximum Likelihood Estimation. The resulted failure probabilities from the degradation model are subsequently used as input for developing the prognostic model.

C. Prognostic Generation Model

The failure probability from the degradation model is stored in the new dataset. The dataset is then divided into two types of dataset for developing the model; training and validating. The training dataset is used into two types of processes. First process determines the network structure while the second process constructs the model with network weights. The validating dataset is used to justify the accuracy of the network. Two measurements are used for validating the model namely RMSE and prediction accuracy which can be defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \bar{x}_t)^2} \qquad (7)$$

$$Accuracy = \left(1 - \frac{|ta - tp|}{ta}\right) \times 100\% \qquad (8)$$

where n is length of time series, x_t represents the observed FP values, x_t represents prediction FP values, t_a is actual failure time and t_p is prediction failure time. After the network model is satisfy, the network will be used for predicting future FP and estimating RUL of equipment.

D. RUL Estimation

In order to give most informative about failure prediction the RUL estimation is generated based on two functions: *d-step prediction* and *predefined z-threshold.* The *d*-step prediction requires the number of multiple time steps in order to extrapolate the failure probability. While predefined *z*-threshold function is proposed in the developed application is to easily the user to generate the duration of RUL based on the range of failure probability level.

V. APPLICATION EXAMPLE

A prognostics application has been developed in order to computerize the proposed method. The application was developed by using MATLAB software due to its capabilities to solve many advanced computational problem with many the establish commands and functions. Furthermore, it offers an interactive GUI-based facility which makes it convenient and easily creates an executable file for practical use.

The developed application has been implemented on an industrial equipment namely autoclave burner. In general, the autoclave burner is used for curing the material such as composite panel in an autoclave. The detail of autoclave process is available in [12]. One of the major failures of the burner is excessive heating oil due to clogging of the carbon black in burner strainer. Based on industrial expertise, oil maximum temperature (*max_temp*) is used as primary condition indictor to control burner performance during operation. In this example, the records of the parameter *max_temp* from January to July 2009 were gathered based on the time curing cycle. These *max_temp* data were transformed into the failure probabilities (FPs) characteristic through the degradation model. After the required failure probability dataset was obtained, FPs are used as input in the feed-forward neural network (FFNN).

In FFNN model construction, the number of the input and hidden neurons should be determined. The FFNN is first trained and tested with one small input neuron and one hidden neuron. The RMSE of every process is recorded with an increased number of the hidden neuron. By using 'forward stepwise' principle, the number of neurons for each layer is determined once the RMSE is less than the next increased of hidden neuron. The overall result revealed that the optimal numbers of input and hidden nodes were 16 and 9 respectively.

With these numbers of neurons and the identified activation function as mentioned in section IV, the FFNN model can be developed. The validating dataset is used in the developed network to predict the failure probability of burner. By choosing function *d-step prediction* or *predefined z-threshold* the predicted FP values and the RUL estimation of burner can be generated. Fig. 4 shows the screenshot of industrial equipment prognostic application.

As an example, this application was used to predict RUL of autoclave burner by using *d*-step prediction strategy. Using the *d*-step prediction, a number of future failure probabilities based on time step can be predicted and extrapolated as shown in Fig 5. Furthermore, the RUL based on the level of failure probability can be calculated.

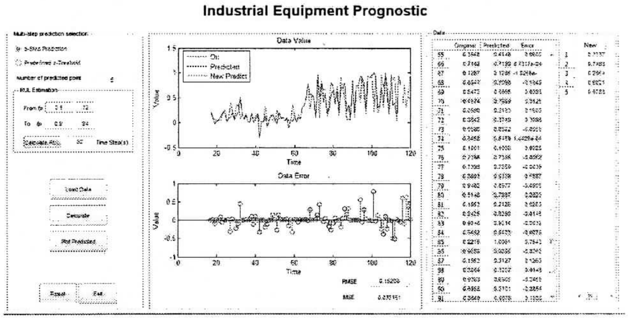

Figure 4. The main screenshot of prognostic application

Data

	Original	Predicted	Error
65	0.3548	0.4148	0.0600
66	0.7182	0.7190	8.7317e-04
67	0.1287	0.1285	-1.9268e-...
68	0.8947	0.7098	-0.1849
69	0.6472	0.6865	0.0393
70	0.4874	0.7999	0.3125
71	0.0580	0.2183	0.1603
72	0.0642	0.3740	0.3098
73	0.0580	0.0522	-0.0058
74	0.8458	0.8459	1.4429e-04

	New
1	0.3337
2	0.7483
3	0.2864
4	0.6021
5	0.9783

Figure 5. The predicted and extrapolated values

Fig.6 shows an example of RUL calculation which indicated that the RUL of autoclave burner level from 0.5 to 0.9 is 62 time steps. In the industry, the result indicated that changing failure probability of autoclave burner from 50% to 90% is approximately 620 hours.

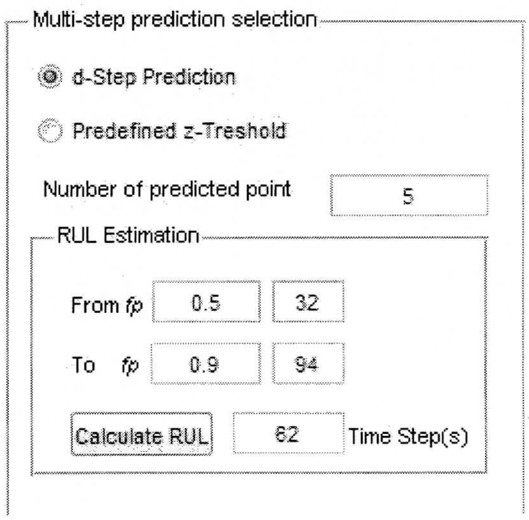

Figure 6. The RUL estimation panel

By having this RUL value in advance, it gives more time to the engineers to plan and decide whether to continue the operation of equipment with high risk of failure or to stop the production and perform maintenance action the equipment.

This type of prediction application can be more attractive when it can be applied for long-range prediction. However, it could contribute larger error due to the usage of prediction value to predict the expected output.

VI. CONCLUSION

Prognostics method has become significantly popular in condition-based maintenance. The primary contribution of this paper is an application of nonlinear prognostics model using neural network with multi step prediction ability. The model utilizes the series of failure probability to estimate the RUL. The use of failure probability in this prognostic model has been found to be useful to characterize the degradation of the observed equipment. With the artificial neural networks and sliding window technique, these failure probabilities have potential to trend the equipment behavior and calculate the remaining useful life estimation for supporting the prognostic ability and assisting maintenance decision making.

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